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# LICENSE PLATE CHARACTER RECOGNITION SYSTEM FROM A BLURRED IMAGE BY USING NEURAL NETWORK

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## ABSTRACT

Recovery of a clear image from a motion blurred image has forever been a rigorous problem in Digital Imaging. Here, we focus on how to recuperate a blurred image due to camera shake. A modified version of the split Bregman method is projected to eradicate motion blurring from the image. The experiments on blurred images show that our algorithm can successfully remove complex motion blurring from natural images with no requirement of any prior information about the motion-blur kernel. From this improved image, license plate region is recognized and plate is extracted. Then character segmentation is performed on extracted License Plate and every single segmented character is recognized by using Neural Network techniques.

**KEYWORDS:** Blind Deconvolution, Motion Blur, Split Bregman, Character Segmentation, Optical Character Recognition

## INTRODUCTION

An image captured by digital camera represents not just the scene at one instant, but the scene over duration of time. If objects in the frame are moving rapidly, the objects or the complete scene will seem to be blurry along the direction of relative motion between the object and the camera. In Digital Imaging, Motion blurring results in poor image quality. Motion blurring is caused mainly due to Camera shake, particularly while taking image by using telephoto lens or using long shutter speed under low lighting condition. In most works till now, Motion blur effect with noise caused due to Camera shake is modeled by a spatial-invariant convolution process, i.e.

$$f = g * p + \eta \tag{1}$$

where "$*$" is the discrete convolution operator, $f$ is the observed blurry image,$g$is the original image to recover, $p$ is the point spread function(or blur kernel ), and ŋ is the noise. The process to recover the original image$g$from the observed image $f$ is the so-called Image deconvolution problem. Based on the presence of $p$, Image deconvolution problems are categorized in two ways. If the blur kernel is specified in prior, recovering the non-blurred image becomes a Non blind deconvolution problem. In the past, there have been extensive research literatures on the robust non blind deconvolution algorithm (e.g., [2]–[7]). If the blur kernel is also unknown, then the process to recover a clear image $g$from the blurred image$f$ is treated as a Blind deconvolution problem. Certain priors on both the point spread function or blur kernel$f$ and the original image$g$ have to be assumed to overcome the ill-effects of motion deblurring. In this paper, we assume that only the significant motion of the camera is a translation along the image plane and that the scene being photographed is static. Let $f$denotes the clear image, and let $g$ denote the observed blurry image due to camera shake.

Then, the relationship between$f$ and$g$ is a convolution processwhich is shown in (1) with the blur kernel $p$ that vanishes out of the camera motion trajectory during the exposure time. [1]

Transportation is a rapidly evolving industry. Recently, Intelligent Transportation System (ITS) has been advanced tremendously. License Plate Recognition (LPR) is an important part of ITS. Character Recognition algorithms for LPR are mainly used for intelligent infrastructure systems like electronic payment systems and freeway and arterial management systems for traffic surveillance. LPR algorithms are generally composed of the following three processing steps: 1) Extraction of location of the license plate (LP) region 2) Segmentation of the Plate characters and 3) Recognition of characters. The first two steps incorporate image processing techniques on still images or frame sequences (videos), whose evaluation relies on the true recognition rate and the error recognition rate. In the past techniques based upon combinations of edge statistics and mathematical morphology have shown very good results. In these method, based on the principle that the change of brightness in the LP region is more remarkable and more frequent than elsewhere the gradient magnitude and the local variance of an image are computed.

An edge based methods when combined with morphological steps that eliminate unwanted edges in the processed images, the LP extraction rate becomes relatively high and fast, compared to other methods and fast, compared to other methods. While recognizing the characters in the first step image enhancement is performed using morphological operations called “top-hat” which is able to locate small objects of significantly different brightness levels. This algorithm, however strongly depends on the distance between the camera and the vehicle, as the morphological operations relate to the dimensions of the binary objects. Then in the next step Sobel Operator is used for edge detection. After edge detection series of morphological operations are performed in order to detect the license plate. Then character segmentation is done using line scanning technique in which scanning is done from left to right of the plate. After Character Segmentation, Features are extracted to obtain the unique features of every character. This paper also gives a small comparison between two Neural Network techniques for character recognition, one is Back Propagation Neural Network and other one is Learning Vector Quantization Neural Network.

## LITERATURE SURVEY

This paper covers the work done on two sections. The first section is mainly associated with the algorithm to obtain deblurred image from a motion blurred image. Second section consists of recognizing the characters of that recovered deblurred image. In the past, there has been extensive research on single-image Blind deconvolution. Early works on blind image deblurring use a single image and assume a prior parametric form of the point spread function, such as the linear motion-blur kernel. These parametric motion-blur kernel models can be obtained by estimating few parameters. To derive the blur kernel some probabilistic priors on natural images edge distributions have been proposed. These methods have certain weakness, either that the assumed probabilistic priors do not always hold true for natural images or that it needs some interactions with the user to obtain an accurate estimation. It is seen that there always have been active research work on multi-image-based Blind motion deblurring methods as multiple images provide more information of the scene and could lead to an easier configuration for accurately estimating point spread function.

Early regularization-based method has to assume all the smooth constraints on images as well as kernels. One such regularization is to use the square norm of image/kernel derivatives as the regularization term on the image/kernel, which is also the so-called Tikhonov regularization method. By considering Gaussian distribution priors, the variational approach is proposed which also assumes the smooth prior of both images and kernels. Moreover, the

parameters involved in the regularization are also automatically inferred by using the conjugate hyperpriors on parameters. [1] To solve various Blind deblurring problems total variation (TV) has been popular choices of the regularization term in recent years. These blind deconvolution techniques have shown good performance on removing certain types of blurring on specific types of images, such as out-of-focus blurring on medical images and satellite images. However, TV regularization is not the optimal choice for removing motion blurring because it penalizes, e.g., the total length of the edges for piecewise constant functions. The support of the resulting blur kernel tends to be a disk or isolated disks.

A more elaborative TV-based model is presented resulting in good performances on removing modest motion blurring from images without rich textures. Moreover, it is dependenton the accurate input of some prior information of the blur kernel. The main drawback of the TV-based regularization for natural images is that they do not store the details and textures very well on the regions of complex structures due to the so-called stair casing effects. Another type of regularization techniques for Blind deconvolution is by using various sparsity-based priors to regularize images, kernels, or both of them.

**Non Blind Image Deblurring Technique**

- **Wiener Filter Deblurring Technique**

The Wiener filter insulates lines in a noisy image by determining an optimal tradeoff between inverse filtering and noise smoothing. It eliminates the additive noise and alters the blurring simultaneously so as to stress any lines which are hidden in the image. This filter operates in the Fourier domain thus removing noise and making it easier as the high and low frequencies are removed from the noise to leave a sharp and clear image. The noise is completely eliminated by using Fourier transform and it becomes easier to isolate the actual line embedded in noise making it more effective method of filtering.

- **Regularized Filter Deblurring Technique**

Regularized filtering is used effectively when inhibitions like smoothness are implied on the recovered image and restricted information is known about the additive noise. The blurred image is restored by a constrained least square restoration algorithm that uses a regularized filter**.** Regularized restoration provides similar results as the Weiner filtering but in regularized filtering less prior information is needed to apply restoration.

- **Lucy-Richardson Algorithm Technique**

This is a non-blind technique of image restoration, used to restore a blurred image that has been degraded by a known blur kernel. It is an iterative procedure in which the pixels of the observed image are represented using the PSF and the latent image as follows:

$$d_i = \sum p_{ij} u_j \quad (2)$$

In equation (2), $d_i$ is the observed value at pixel position $i, p_{ij}$is the PSF,$u_j$is the latent image pixel value at location $j$. [10]

- **Blind Image Deblurring Technique**

In this technique we have to estimate the blur kernel i.e. point spread function and then using that estimate we have to deblurr the image. This method is performed iteratively as well as non-iteratively. Considering the iterative approach,

after each iteration the estimate of PSF is improved and by using that we can improve the resultant image repeatedly by bringing it closer to the original image. In the Non-iterative approach one application of the algorithm based on exterior information extracts the PSF and this PSF is used to restore the non-blurred image from a degraded image.

## PROPOSED SYSTEM

The original image is intentionally blurred using degradation model to produce the blurred image. The blurred image should be an input to the deblurring algorithm. Various algorithms are available for deblurring. In this paper, we are going to use blind deconvolution algorithm. The result of this algorithm produces the deblurring image which can be compared with our original image.

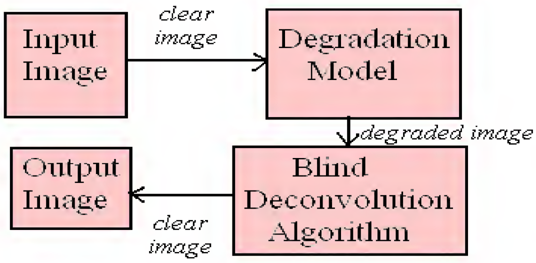


**Figure 1: Block Diagram of the Proposed System**

### Identifying Blur Using Image Statistics

Given an image, the motion blur direction can be selected as the direction with minimal derivatives variation. For the plainness of the derivation we will assume here that the direction of the motion blur is horizontal, and that the image contains a single degraded object plus a non-blurred background. This is done to determine the size of the blur kernel. For that we figure the histogram of horizontal derivatives within the image. However, complete image is not blurred. There is no single blurring model that will describe the observed his to gram without segmenting the blurred area. Instead, we try to describe the observed histogram with a mixture model.

### Segmenting Blur Layers

After finding the blurring kernel $f$, we can use it to deconvolve the image. This brings significant improvement in the blurred areas within the image. Serious artifacts are observed in the background. Therefore, in addition to recovering the blurring kernel, there is a requirement to segment the image into blurred and non-blurred layers. We search for a smooth segmentation that will maximize the likelihood of the derivatives in each region.

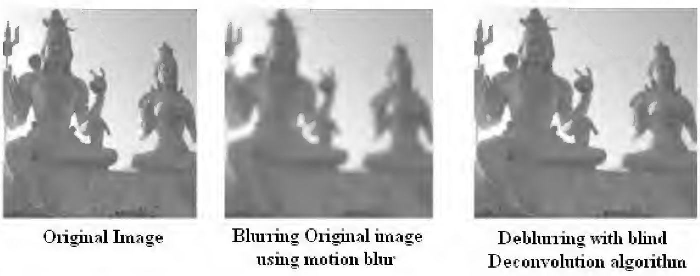


**Figure 2: Segmenting Blur Layers**

We propose a new optimization approach to remove complex motion blurring from a single image by introducing new sparsity-based regularization terms on both images and motion-blur kernels. Our approach is related to recent works

on both blind image deconvolution and non blind motion deblurring. Two non blind image deconvolution algorithms are both based on the observation that images usually have sparse representations in some redundant transform domain, e.g. wavelet and framel et transforms. Given the blur kernel, $p$ is solved by seeking a sparse solution in the corresponding transformed domain. The difference between two methods mainly lies in the approaches to enforce the sparsity prior; one is by using the so-called synthesis-based sparsity prior, and the other is by using the so-called analysis-based sparsity prior.

Given a blurred image satisfying relationship (1), we take a regularization-based approach to solve the blind motion deblurring problem, which requires the simultaneous estimations of both the original image and the blur kernels. It is well known that the challenging non convex minimization problem can be solved by regularization-based blind deconvolution approach. The most commonly used approach is an alternative iteration scheme which is described in Algorithm 1.

**Algorithm 1: Outline of the Alternative Iterations**

For k=0, 1…

- Given the PSF or blur kernel $p^{(k)}$, we compute the Deblurred image $g^{(k+1)}$, i.e.,

$$g^{(k+1)} = \arg_g \min \frac{1}{2}\left\|p^k * g - f\right\|_2^2 + \lambda_1\Theta_1(g)$$

Where the regularization term on images is given by $\Theta_1(\cdot)$and $\lambda_1$ is the corresponding regularization parameter.

- Given the clear or Deblurred image $g^{(k+1)}$, we compute the blur kernel or PSF $p^{(k+1)}$, i.e.,

$$p^{(k+1)} = \arg_p \min \frac{1}{2}\left\|g^{(k+1)} * p - f\right\|_2^2 + \lambda_2\Theta_2(p)$$

Where the regularization term on kernels is given by $\Theta_2(\cdot)$and $\lambda_2$ is the corresponding regularization parameter.

Algorithm 1 consists of two steps and both steps are associated with regularization-based approach for non blind deconvolution. Step 1 is a non blind image deblurring problem, which has been extensively practiced in the literature. However the estimated blur kernel used for deblurring in step 1 is not accurate and it is far away from the truth during the initial iterations. Inspired by the strong noise robustness of the recent non blind deblurring technique, we also use the analysis sparsity prior on the original image under the frame let system to regularize the non blind image deblurring to lessen the distortion caused by the in correct intermediary estimate of the blur kernel.

**Numerical Algorithm**

This is committed to the comprehensive numerical algorithm of our blind motion deblurring algorithm outlined in Algorithm 1. Both steps in Algorithm 1 are solving the identical type of large-scale minimization problems. One efficient solver for minimizations concerning such terms is the split Bregman iteration which we will use in our solver. The Bregman iteration was first introduced for non-differentiable TV energy and was then effectively applied to wavelet-based denoising. To further progress the performance of the Bregman iteration, a linearized Bregman iteration was invented. More information and an enhancement called "kicking" of the linearized Bregman iteration are described, and a meticulous theory was given. The linearized Bregman iteration for frame-based image deblurring was proposed. Recently, a new type of iteration based on the Bregman distance, called split Bregman iteration, was introduced in [2], which extended the utility of the Bregman iteration and the linearized Bregman iteration to more general -norm minimization

problems. The basic idea of split Bregman iteration is to renovate the unrestrained minimization problem (Algorithm 1) into a constrained one by introducing an auxiliary variable and then invoke the Bregman iteration to resolve the constrained minimization problem. Numerical simulations illustrate that it converges quickly and only uses a small memory footprint, which make it very attractive for large-scale troubles.

- Set $k = 0, p^{(0)} = \delta, d_1 = b_1 = 0$, and $d_2 = b_2 = 0$,

  Where $\boldsymbol{\delta}$ is delta function;

- DO

  $g^{\left(k+\frac{1}{2}\right)} = \arg\min_g \frac{1}{2}\left\|\left[p^{(k)}\right] * g - f\right\|_2^2 + \frac{\lambda_1\mu_1}{2}\left\|Wg - d_1{}^{(k)} + b_1{}^{(k)}\right\|_2^2$

  $g^{(k+1)}(j) = \begin{cases} 1, if g^{\left(k+\frac{1}{2}\right)}(j) > 1; \\ 0, if g^{\left(k+\frac{1}{2}\right)}(j) < 0; \\ g^{\left(k+\frac{1}{2}\right)}(j), otherwise \end{cases}$

  j=1, 2…N

  $d_1{}^{(k+1)} = \frac{T_1}{\mu_1}\left(Wg^{(k+1)} + b_1{}^{(k)}\right)$

  $b_1{}^{(k+1)} = b_1{}^{(k)} + (Wg^{(k+1)} - d_1{}^{(k+1)})$

  $p^{(k+1)} = \arg\min_p \frac{1}{2}\left\|g^{(k+1)} * p - f\right\|_2^2 + \frac{\lambda_2\tau}{2}\|p\|_2^2 + \frac{\lambda_2\mu_2}{2}\left\|Wp - d_2{}^{(k)} + b_2{}^{(k)}\right\|^2$

  $\tilde{p}^{(k+1)}(j) = \max\left(p^{\left(k+\frac{1}{2}\right)}(j), 0\right), j = 1,2, \dots, N$

  $p^{(k+1)} = \frac{\tilde{p}^{(k+1)}}{\|\tilde{p}^{(k+1)}\|_1}$

  $d_2^{(k+1)} = \frac{T_1}{\mu_2}(Wp^{(k+1)} + b_2^{(k)})$

  $b_2{}^{(k+1)} = b_2^{(k)} + (Wp^{(k+1)} - d_2{}^{(k+1)})$

  $k = k + 1$

  UNTIL (k≥ $K or \left\|p^{(k)} - p^{(k-1)}\right\|_2^2 \le \xi$

  Once the deblurred image is obtained, Character Recognition is done by following steps:

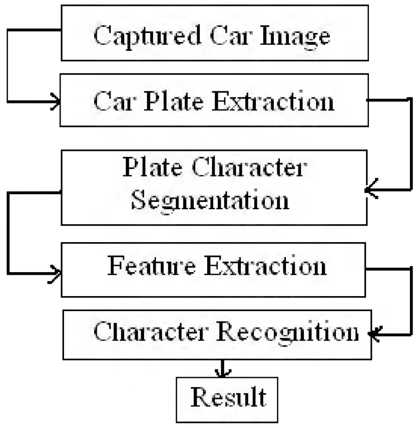


**Figure 3: License Plate Character Recognition**

**Plate Extraction**

Image Preprocessing operations are performed on the original car image to enhance the quality of car image for better results in further operations on the Number plate. "A License Plate Locating Method Based on Tophat-Bothat Changing and Line Scanning" [11], introduces the whole method of image preprocessing and of plate region exposure. By using an image collection card the captured images are converted to digital form. This image is then converted to a gray scale image. The subsequent step is image pre-processing for which Top-hat and Bot-hat procedure is used. This technique improves the in general contrast of the image. After enhancing image, License Plate Detection is done using various morphological operations [12].


**Figure 4: Plate Extraction**

**Character Segmentation**

The License plate obtained after Plate Extraction process has characters is gray-scale. To segment the characters, first plate image is transformed into binary image. Then 'Lines' Function is used to split text on the number plate into lines, which uses 'clip" function'. Clip" function crops black letter with white background. Once the image is cropped, resizing is done and same operation is continued on the cropped image. This procedure is followed until all the characters are segmented.

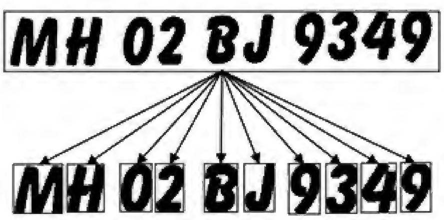


**Figure 5: Character Segmentation**

### Feature Extraction

Neural Network is used for character recognition in this paper; Feature Extraction is a significant step for training and simulating the Neural Network. Feature Extraction is performed on every segmented character. Two feature extraction techniques are practiced for training and simulating Neural Network. One is Fan-beam Transform and other technique is based on Character Geometry. Fan-beam Transform is used for computing an optional mathematical representation of an image by means of Fan-beam projections. Fan-beam function computes projections of an image matrix all along specified directions. Projection of two dimensional function f(x, y) is a set of line integrals.

The line integrals are computed along paths that radiate from a single source, forming a fan shape by applying the Fan beam function. To represent an image, this function takes multiple projections of the image from different angles by rotating the source (angle is assumed to be 100) around the centre of the image. The distance between the fan-beam vertex and the center of rotation (center pixel of the image) is fixed for all projections (distance is assumed to be 200 pixels), this distance must be large enough to ensure that the fan-beam vertex is outside of the image at all rotation angles. There are 15 sensors spaced uniformly along a circular arc for each projection. 36 projections are required to cover 360 degrees with 100 rotation angle. Thus column of fan beam data (features) of the image is 540 sensor samples. “A Feature Extraction Technique Based on Character Geometry for Character Recognition” [13] describes a geometry based technique for feature extraction. The column of features for Character Geometry based feature extraction has 55 values.

### Character Recognition

Character Recognition step is the final and main part of this system, where segmented characters are recognized. Conventional methods used for Character recognition were OCR “Optical Character Recognition” and “Formula Based Recognition”. As Neural Network” is an intelligence engine, it ensures greater accuracy rate along with better recognition speed. Two neural network techniques are extensively practiced for character recognition: BP ANN (Back Propagation Artificial Neural Network) and LVQ NN (Learning Vector Quantization Neural Network), after recognizing the characters of the plate by these two methods, voting can be performed to find out the best method depending upon the time taken and accuracy.

## EXPECTED RESULTS

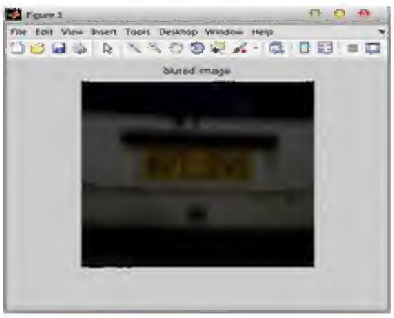

Figure 6: Blur Image

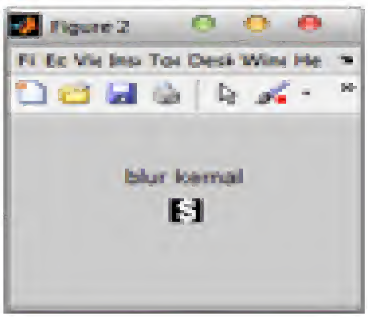


Figure 7: Blur Kernel


Figure 8: Deblurred Image


Figure 9: License Plate Recognized

## CONCLUSIONS

In this paper, a new algorithm has been presented to remove camera shake from a single image of license plate. Depending on the analysis-based sparsity prior of images in the frame let domain and a mixed regularization on motion-blur kernels, which includes both the analysis-based sparsity prior of kernels in the frame let domain and the smoothness prior on kernels, our new formulation onmotion deblurring has led to a powerful algorithm that canrec over a clear image from a given motion-blurred image. And from the derived deblurred image we have recognized the number plate by using neural network.

## REFERENCES

1. Jian-Feng Cai, HuiJi, Chaoqiang Liu, and ZuoweiShen, "Framelet-Based Blind Motion Deblurring From a Single Image", IEEE Transction Paper on Image Processing, vol. 21, no. 2, February, 2012.
2. J.-F. Cai, S. Osher, and Z. Shen, "Split Bregman method and frame based image restoration," Multisc. Model. Simul., vol. 8, no. 2, pp.337–369, 2009.
3. H. C. Andrews and B. R. Hunt, Digital Image Restoration. Engle wood Cliffs, NJ: Prentice-Hall, 1977.
4. M. K. Ng, R. H. Chan, and W. Tang, "A fast algorithm for deblurring models with Neumann boundary condition," SIAM J. Sci. Comput., vol.21, no. 3, pp. 851–866, Nov./Dec. 1999.
5. T. F. Chan and J. Shen, Image Processing and Analysis, ser. Variational, PDE, Wavelet, and Stochastic Methods. Philadelphia, PA: SIAM, 2005.
6. Chai and Z. Shen, "Deconvolution: A wavelet frame approach, "Numer. Math., vol. 106, no. 4, pp. 529–587, May 2007.
7. Y. Lou, X. Zhang, S. Osher, and A. Bertozzi, "Image recovery via nonlocal operators," J. Sci. Comput., vol. 42, no. 2, pp. 185–197, Feb.2010.
8. Anuja P. Nagare,"License Plate Character Recognition System using Neural Network", International Journal of Computer Applications (0975 – 8887),Volume 25– No.10, July 2011.
9. Amandeep Kaur and Vinay Chopra," A Comparative Study and Analysis of Image Restoration Techniques Using Different Images Formats", International Journal for Science and emerging Technologies with Latest Trends, 2(1):7-14(2012).

10. D. C. Dobson and F. Santosa, “Recovery of blocky images from noisy and blurred data,” SIAM J. Appl. Math., vol. 56, no. 4, pp. 1181–1198, Aug. 1996.

11. P G Hou, J Zhao and M Liu, “A License Plate Locating Method Based on Tophat-bothat Changing and Line Scanning”, In Proc. of International Symposium on Instrumentation Science and Technology, 2006, pp. 431–436.

12. Antonio Albiol, Jose Manuel Mossi, Alberto Albiol, Valery Naranjo, “Automatic License Plate Reading Using Mathematical Morphology”, In proc. of Spanish Ministry of Science and Technology, 2002.

13. Dinesh Dileep, “A Feature Extraction Technique Based On character Geometry for Character Recognition”, in proc. Of Department of Electronics and Communication Engineering, Amrita School of Engineering, pp. 1-4.